FAILURE MODE IDENTIFICATION THROUGH CLUSTERING ANALYSIS

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ABSTRACT

Research has shown that nearly 80% of the costs and problems are created in product development and that cost and quality are essentially designed into products in the conceptual stage. Currently failure identification procedures (such as FMEA, FMECA and FTA) and design of experiments are being used for quality control and for the detection of potential failure modes during the detail design stage or post-product launch. Though all of these methods have their own advantages, they do not give information as to what are the predominant failures that a designer should focus on while designing a product. This work uses a functional approach to identify failure modes, which hypothesizes that similarities exist between different failure modes based on the functionality of the product/component. In this paper, a statistical clustering procedure is proposed to retrieve information on the set of predominant failures that a function experiences. The various stages of the methodology are illustrated using a hypothetical design example.

INTRODUCTION

Identification of potential failure modes during the product design process is critical for creating failure-free designs. Currently industries use procedures such as Failure Modes and Effects Analysis (FMEA), Fault Tree analysis, or Failure Modes, Effects and Criticality analysis (FMECA), as well as prior knowledge and experience, to determine potential failure modes. These procedures require designers to have a broad knowledge of commonly occurring failure modes and to understand any connections (causality) between failures for successful implementation. If there is a lack of sufficient knowledge to predict all of the realistically possible failure modes, then the current failure prevention procedures may fail.

To increase the effectiveness of failure identification and prevention procedures, we build on a function-failure method introduced by Tumer and Stone [1] where functionality is used to guide the determination of potential failure modes a product may be subject to, once placed in its operating environment. In this paper, this work is extended to explore the statistical characteristics of failure modes by means of clustering methods, using the set of failure modes and functions generated in Arunajadai et al. [2]. Using the results of the cluster analysis, a methodology is proposed to identify potential failures in the conceptual design stages. The following subsections first describe the function-failure method briefly, followed by a discussion of how failure is documented, and some background on statistical means to

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retrieve failure information. Then, a detailed discussion of a functional approach to study potential failure modes is presented, where an investigation of failure distributions is used as the basis for the proposed clustering approach. The main contribution of this paper is the clustering approach to study potential failure modes, which is presented in detail next, including some background on clustering techniques, and application to a hypothetical design example.

The Function-Failure Method as a Step toward Failure-Free Design

Standardization of a product function vocabulary to enable archival and retrieval of product design knowledge has been a primary research area for many years now [3-6]. In this work we use the functional basis developed by Hirtz et al. [3] and Stone and Wood [6] to link failure back to the more abstract product function. Similar work has been suggested for the classification of failure modes. Collins [7] has described 23 different mechanical failures based on the characteristics of the manifestation of failure, the failure inducing agent and the location of failure. There are other classifications like those based on the end effect of the failure [8] and the design stage in which the failure mode might have been introduced [9]. Our current work starts with the Collins classification and augments it such that each failure mode is identified with the help of a primary and secondary identifier [1, 2].

This work employs a functional approach first introduced by Tumer and Stone [1], and explored further by Arunajadai et al. [2] and Roberts et al. [10]. It uses matrices to record data describing the functionality of components (the function-component matrix, **EC**) and failure modes observed in components (the component-failure matrix, **CF**). The functional basis is employed to describe functions and the failure classification to describe failure modes. Through a matrix multiplication, the function-failure matrix **EF** is obtained to link failure mode information to a functional description. The mathematical formulation is:

$$\mathbf{EC} \times \mathbf{CF} = \mathbf{EF}. \qquad (1)$$

Documenting Failure

Over the years many procedures have been developed to document failure data. Notable among them are the Failure Mode and Effects Analysis (FMEA), Failure Modes Effects and Criticality Analysis (FMECA) and the Fault Tree Analysis (FTA). In this work we take a new look at the principles of FMEA and present a methodology for failure-free design of products.

The FMEA procedure is an offshoot of the Military procedure MIL-P-1629 [11] developed by the United States Military as a tool to determine and evaluate equipment failures. Many industries have developed their own standards of performing the FMEA like the AIAG (1993) of the Automotive Industry Action Group, MIL-STD-1629A (1984) of the US Department of Defense, SAE J1739 (1994) of the Society of Automobile Engineers and the VDA 96, Heft4, Teil 2 (1996) of the Verband der Automobileindustrie, Germany.

The Traditional FMEA when performed rigorously contains valuable information about the failures of various components but has two fundamental weaknesses – lack of a methodological guideline to conduct the FMEA and the employment of natural language in recording the information [12]. Current Industrial FMEA practice is severely restricted in its usefulness and analytical power because of limitations of spreadsheet based approaches to acquiring, representing and reasoning with system failure knowledge. Thus the standardization of the failure mode vocabulary would make the procedure more useful and repeatable.

In this work, we use a matrix-based method to help sort through the failure modes associated with products. A matrix approach to recording failure data was introduced as early as 1976 by Collins et al. [13] and the concept of applying matrix techniques to FMEA was introduced in 1977 by Barbour [14] and subsequently developed by Goddard and Dussault [15]. More recently the matrix technique has been employed by Henning and Paasch [16] to represent the failure and replacement characteristics of a system.

Retrieving Failure Information – The Statistical Approach

Statistical tools have been employed for some time now in quality control and reliability measurement. A structural approach based on probability theory for the design and safety analysis of aircraft began in the early 1960s [17]. The use of numerical probabilities may not be a prerequisite for carrying out system safety analyses, but it provides valuable guidance to the designer in determining the architecture required and assessing its failure tolerance. The prediction of system failure probabilities is not a precise science, however the process does provide an extremely good framework on which to hang engineering experience [17]. Lee [18] has employed the Bayes networks to account for the conditional dependencies between states and events in the causal chain and across causal chains. This approach constitutes a mathematically sound method for representing and reasoning with joint probability distributions in an internally consistent manner. Traditional FMEA ignores these connections and implicitly assumes that all failure states and events, together with their causes and effects, are probabilistically independent.

Probabilistic design is concerned with the probability that a system will realize the function assigned to it without failure. Onyebueke et al. [19] give an overview of the Probabilistic Design Methodology (PDM) with emphasis on the quantification of the effects of uncertainties for the structural variables and the evaluation of failure probabilities. PDM takes into consideration reliability, optimization, cost parameters and the sensitivity of design parameters, which is ignored by the deterministic method and is extremely useful in designs characterized by complex geometry, sensitive loads and material properties. The method is limited in use due to three identifiable factors: 1) most people are unaware of the capabilities of the PDM and the available computer codes; 2) there is not yet a universal decision as to what constitutes an acceptable risk; and 3) there is very little information on most design parameters [19].

Bhonsle et al. [20] have developed a statistical distribution function called adaptive distributive function model which is compatible with collected data and produces conservative designs at low tail ends. Meeker and Hamada [21] discuss the role of statistical process monitoring and designed experiments as tools for quality improvement. They also differentiate between the traditional reactive approach where the reliability requirements are not met at the time of delivery of the product and the proactive reliability assurance approach. Yang and Xue [22] describe the application of the fractional factorial design of experiment method to degradation testing and reliability design. Marco et al. [23], while describing the integration of the FMEA and serviceability design, raise the need for calculating statistical and probabilistic occurrence measures for each type of failure mode depending on component type, operational environment or duty cycle.

Key Issues

The functional approach toward failure-free design, used in this paper, provides a systematic methodology for storing and exploring function and failure data in an informative way. Apart from providing a means to store data in a standardized vocabulary, it also helps in storing data that is more conducive to statistical or other kind of analyses. Most statistical tools developed over the years for reliability design have been important tools in designing reliable products. However their use and repeatability has been severely hampered by their non-standardized ways of describing failure modes or their effects or causes. This difficulty is aggravated by the often powerful but complex statistical computations.

This paper addresses these key issues by proposing a statistical cluster analysis approach, described in the following sections.

FAILURE MODES STUDY – A FUNCTIONAL APPROACH

The failure-function approach described in [1, 2, 10] is used as a starting point in this research work. This method provides a standardized vocabulary to record failure data and a matrix approach to store failure information, which helps in easy retrieval of data and aids in further calculations of similarities between designs and failure modes, with the purpose of eliminating operational failures. In this paper we go one step further to show how the matrix approach aids in identifying critical failure modes and functions, by making use of the probabilistic characteristics of the observed failure modes.

General Observations

We know by experience that certain failure modes occur more frequently than the others. The question we want to answer is: given a function of a product, are there failure modes that are more likely to occur than others? Such information would be of immense importance in the conceptual design stage, allowing the designer to take appropriate measures to ensure the best possible design. It is our hypothesis that if the failure mode occurrence knowledge is easily accessible, the designer can focus on the appropriate analyses to prevent the failure modes.

To test this hypothesis we examined a set of 41 consumer products through laboratory testing (following the reverse engineering technique of Otto and Wood [25] to document component function and failure mode). The following observations were made from the three resulting matrices: 1) **EC**, the function-component matrix; 2) **CF**, the component-failure matrix; and 3) **EF**, function-failure matrix that are generated as a part of the functional approach.

Distribution of Failure Modes: The total number of occurrences of each failure mode was calculated from the component-failure (**CF**) matrix. A Pareto chart was plotted for the occurrence of the failure modes and is shown in Figure 1.

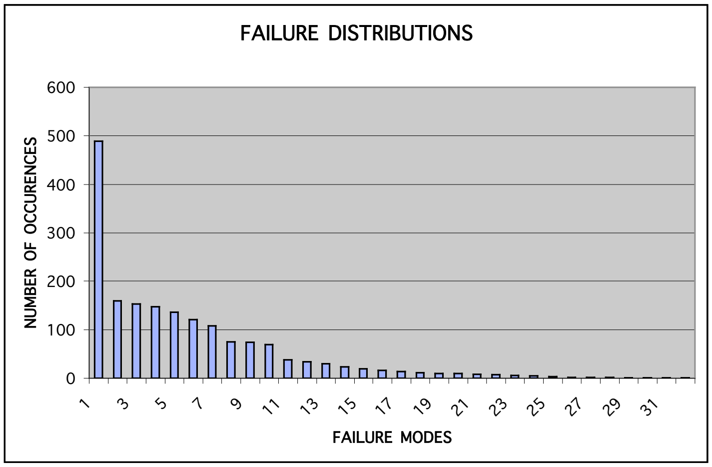

Figure 1. Failure Mode Distributions.

It is evident from the graph that certain failure modes occur more frequently than the others. In fact 92% of the failures were accounted by just 40% of the failure modes, i.e., 92% of the failures were contributed by just 13 of the 32 failure modes. Thus by concentrating on these failure modes, the designer can be assured that the major failure types have been taken care of. To verify this fact we checked the component-failure matrix to see the number of failure modes that were overlooked per component. Of the 1001 components in the matrix only 134 of them exhibited failure from the 19 infrequently occurring failures. Of these 134 components only 8 of them exhibited 2 of these 19 failure modes and the rest just 1 of the 19 failure modes. Thus, on an average for the 1001 components, we overlooked 0.141 failure mode per component belonging to the 19 less frequently occurring type. This was calculated by determining the number of failure modes that were not addressed for a component after taking into account the 13 primary failure modes. Then the average was calculated for the 1001 components.

Distribution of Failures Across Functions: The sum of each row corresponding to the given function in the function-failure (**EF**) matrix gives the number of failures experienced by the function for the time period observed. A Pareto chart was plotted for the number of failures for a given function and is shown in Figure 2.

As seen from Figure 2, there are certain functions that exhibit more failures both in type of failures and the number of occurrences. Only 42 of the 180 functions experienced at least 1% of the failures. Thus the designer can focus his time and money on these functions that are more critical in design than the others.

Number of distinct failure modes with increasing functions: As the number of functions increase, the number of distinct failure modes that are contributed by the new function decreases. That is, there is a limit after which the addition of a new function does not contribute a new distinct failure mode. This fact reinforces the hypothesis that the designer can concentrate on a particular set of failure modes, as the additional functions are very unlikely to add a substantial number of new distinct failure modes. Figure 3 shows the plot of the number of distinct failure modes with increasing number of functions. It is seen that there are no new failure modes observed after 9 functions.

Number of distinct failure modes with increasing components: As with the functions, as the number of component increase, the number of new distinct failure modes observed in a component decreases. That is, as the number of components increase, the probability that it would experience a new distinct failure decreases. As shown in Figure 4, the number of distinct failure modes observed decreases as the number of components increase.

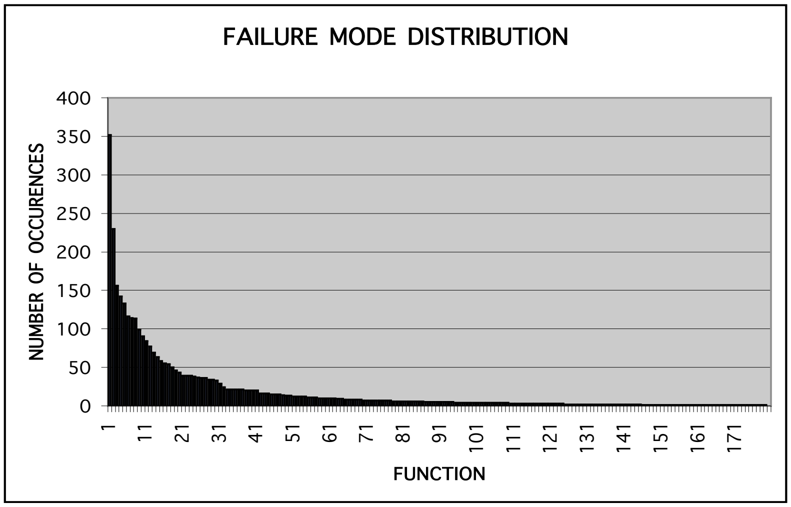

Figure 2. Failure Modes for a Given Function.

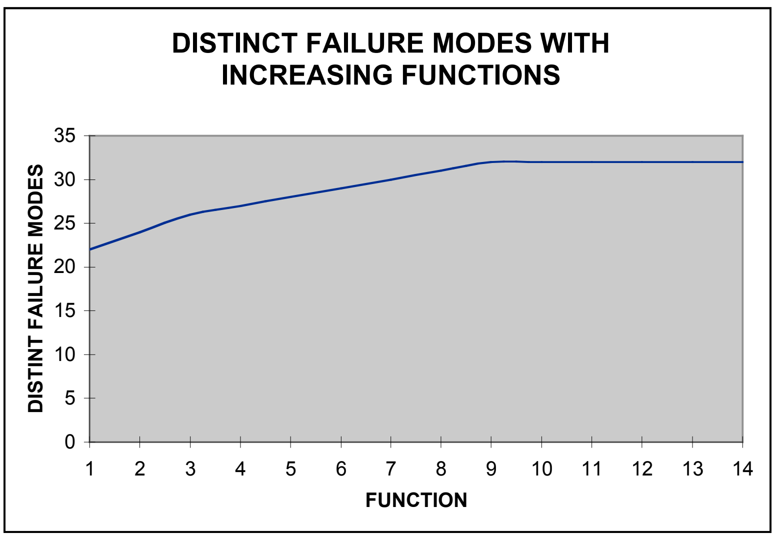

Figure 3. Distinct Failure Modes with increasing functions.

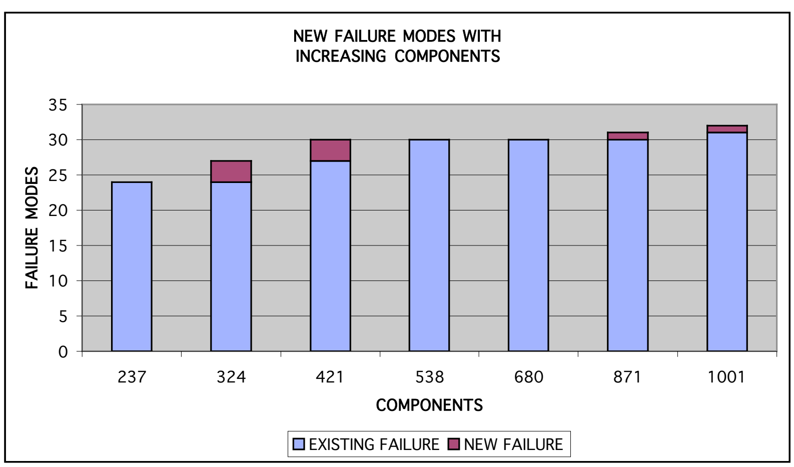

Figure 4. Distinct failure modes with increasing components.

Present scope of research

To summarize, our empirical study of 41 products provides a reliable knowledge base on which to propose a new statistically-based approach toward failure free design. The addition of new components or new functionality is not expected to significantly alter our findings. For this paper, we only focus on the failure mode occurrence data. While typical FMEA approaches also include severity and detectability data, we will be confined to occurrence data and the inherent statistical knowledge it holds.

FAILURE MODES STUDY – A CLUSTERING APPROACH

Time is money. This is all the more true for product development in today's highly competitive market. Thus the key to success is to get the product to the customer in the shortest possible time ensuring maximum performance and safety. The issue is whether this can be accomplished without a substantial increase in cost of product development.

Let us examine a simple hypothetical design situation. Assume a product in which the function *Stop Gas* is involved. Using the concept generator approach, by pre-multiplying the function-component (EC) matrix by an appropriate filter matrix, we obtain the morphological matrix containing possible component solutions to the function [1, 2, 26]. We present here the morphological matrix pertaining to the function *Stop Gas* in Table 1.

Table 1. Morphological Matrix for the Function *Stop Gas*.

FUNCTION / COMPONENT	RUBBER PISTON SEAL	O-RING	RUBBER SEAL PLUG	AIR TUBE CAP	RUBBER PRESSURE GAUGE RING	SPACER	RUBBER BARREL SEAL
STOP GAS	1	1	1	1	1	1	1

Though it is not necessary for a designer to use the component solutions obtained from the morphological matrix, here we select the solution of using some kind of a rubber seal to accomplish the function *Stop Gas*. The designer's decision of which failure modes should be the focus of the analysis depends on the application– it could be a simple home-product where the seal just acts as an obstruction for stagnant air or the highly complex aerospace industry products where the seal might have to stop the flow of gas at high pressure and temperature. Let us refer to the function-failure matrix (EF) to know what kind of failure modes are exhibited by the function *Stop Gas*. The reduced EF matrix with the failures corresponding to the function *Stop Gas* alone is shown in Table 2.

Table 2. EF Matrix for the function *Stop Gas*.

FUNCTION / FAILURE MODE	ABRASIVE WEAR	BRITTLE FRACTURE	COMPRESSION SET	CORROSIVE WEAR	CRACKING	DEFORMATION WEAR	DIRECT CHEMICAL ATTACK	FORCE INDUCED DEFORMATION	HEAT CRACKING	HIGH CYCLE FATIGUE	INSTALLATION DAMAGE	TEMPERATURE INDUCED DEFORMATION	YIELDING
STOP GAS	1	0	3	0	1	0	0	4	0	0	1	0	0

We see that the function *Stop Gas* has experienced 5 distinct failure modes for the time period observed. The question now is whether the designer should concentrate on all the failures during design. In this rather simple case, the difference between designing for 5 failures and 3 failures may seem trivial. But consider cases where a function exhibits 15 different kinds of failures or for multiple functions of a product. It would be of great advantage to know if there is a particular set of failures that a designer could concentrate on which could ensure safety of the product and, at the same time, save cost and reduce time of product development. The next section explains a cluster analysis approach that would help extract the information as to the set of failure modes that a designer can concentrate on.

Background: Cluster Analysis

Cluster analysis is a multivariate statistical procedure that starts with a data set containing information about a sample of entities and attempts to reorganize these entities into relatively homogeneous groups. It is helpful when a researcher tries to classify or group data into categories or groups when neither the number of groups, nor the members of the group are known. Clustering has proved to be good technique to be used in exploratory data analysis when it is known that the sample is not homogeneous [24].

There are two main methods by which clustering analysis is performed – Hierarchical clustering and K-means clustering. In this paper we have used the hierarchical clustering as the number of cases is small (32 failure modes); the K-means method is more advantageous when there are a large number of cases (greater than 200). In the hierarchical method, clustering begins by finding the closest pair of objects, according to a distance measure and combines them to form a cluster. The algorithm continues one step at a time, joining pairs of cases, pairs of clusters, or a case with a cluster, until all the data are in one of the clusters. The method is hierarchical because, once two cases or clusters are combined, they remain together until the final step. The hierarchical clustering offers several methods for combining or linking clusters. In this work we have used the complete linkage method [24].

The complete linkage method rule states that any candidate for inclusion into an existing cluster must be within a certain level of similarity to all members of that cluster. This rather rigorous rule of the complete linkage method has a tendency to find relatively compact, hyperspherical clusters composed of highly similar cases.

The disadvantage of the cluster analysis is that, though the algorithm helps in forming the clusters, the final decision as to how many clusters and the membership of the cluster is dependent on the researcher's judgment. Most algorithms cluster the cases according to the number of clusters input by the user. The user performs this a number of times and with the help of other indicators like dendograms, a tree diagram that depicts the clustering sequence, decides which is the best set of clusters. However the method acts as a useful starting point for grouping data, especially when the data space is too large to analyze.

Technical Approach

As described in the previous sections, the cluster analysis is a multivariate statistical procedure that helps to group or categorize data. Our attempt is to group failure modes based on their occurrence data – i.e., we would like to have the information as to whether the failure is to be considered by itself or whether it has a tendency of accompanying other kinds of failure. The cluster analysis is performed using the SPSS software. The software gives different cluster combinations and the research team interpreted the clusters and decided upon the best number of clusters and their membership. To get the failure mode groupings, the cluster analysis is performed on the failure similarity matrix, which is obtained by pre-multiplying the component-failure matrix (**CF**) by its transpose [1]. The similarity matrix, shown in Figure 5, follows from the matrix multiplication:

$$\square = \mathbf{CF}^{T} \times \mathbf{CF}. \qquad (2)$$

The hierarchical clustering algorithm using the complete linkage method was performed on the data. The software grouped the data into clusters ranging in from 6 clusters to 15 clusters with minor variations at each stage. The different cluster combinations were studied and the number of clusters for this set of data was fixed at 9 based on engineering judgment. Thus we have grouped the 32 failure modes identified in this work into 9 groups as shown in Table 3.

FAILURE / FAILURE - (COMP)	ABRASIVE WEAR	ADHESIVE WEAR	AGEING	BIOLOGICAL CORROSION	BLISTERING	BRITTLE FRACTURE	COMPRESSION SET	CORROSIVE WEAR	CRACKING	CREEP BUCKLING	CREEP STRESS RUPTURE	DEFORMATION WEAR	DIRECT CHEMICAL ATTACK	DUCTILE RUPTURE	FORCE INDUCED DEFORMATION	FRETTING FATIGUE	GALLING AND SEIZURE	GALVANIC CORROSION	HEAT CRACKING	HIGH CYCLE FATIGUE	IMPACT DEFORMATION	IMPACT FRETTING	IMPACT FATIGUE WEAR	INSTALLATION DAMAGE	INTERGRANULAR CORROSION	STARVED JOINT	SURFACE FATIGUE WEAR	TEMPERATURE INDUCED DEFORMATION	THERMAL FATIGUE	THERMAL RELAXATION	THERMAL SHOCK	YIELDING
ABRASIVE WEAR	74	0	1	0	0	5	2	4	6	0	0	3	18	0	15	0	0	0	2	5	0	0	0	1	1	0	1	9	0	1	0	5
ADHESIVE WEAR	0	121	0	0	0	0	0	0	0	0	0	101	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	10
AGEING	1	0	14	0	0	0	0	0	8	0	0	0	0	0	6	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
BIOLOGICAL CORROSION	0	0	0	1	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BLISTERING	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BRITTLE FRACTURE	5	0	0	0	0	34	0	11	0	0	0	0	1	0	4	0	3	0	0	10	0	0	0	0	0	0	1	21	0	0	4	5
COMPRESSION SET	2	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
CORROSIVE WEAR	4	0	0	1	0	11	0	75	2	0	0	7	30	0	31	1	1	0	0	10	0	0	1	0	0	0	0	17	3	0	1	23
CRACKING	6	0	8	1	0	0	0	2	147	0	29	6	11	0	102	0	11	0	0	21	1	0	0	0	0	0	12	4	0	0	0	0
CREEP BUCKLING	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
CREEP STRESS RUPTURE	0	0	0	0	0	0	0	0	29	0	38	0	6	0	30	0	11	0	0	16	0	0	1	0	0	0	13	0	0	0	0	0
DEFORMATION WEAR	3	101	0	0	0	0	0	7	6	0	0	153	2	1	23	0	0	0	0	2	2	0	1	0	0	0	0	2	0	2	0	8
DIRECT CHEMICAL ATTACK	18	2	0	1	0	1	0	30	11	0	6	2	108	0	54	0	0	0	1	1	0	0	1	1	1	0	0	11	3	0	3	16
DUCTILE RUPTURE	0	0	0	0	0	0	0	0	0	0	0	1	0	8	6	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	5
FORCE INDUCED DEFORMATION	15	2	6	0	0	4	0	31	102	1	30	23	54	6	489	0	14	0	0	24	10	0	7	0	2	0	25	19	2	5	3	50
FRETTING FATIGUE	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
GALLING AND SEIZURE	0	0	0	0	0	3	0	1	11	0	11	0	0	0	14	0	19	0	0	16	0	0	0	0	0	0	14	4	0	0	0	1
GALVANIC CORROSION	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	1	0	0	3	0	0	0	0
HEAT CRACKING	2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	1	0	0	0	0	0	0	0	0
HIGH CYCLE FATIGUE	5	0	0	0	0	10	0	10	21	0	16	2	1	1	24	0	16	0	0	69	0	0	0	0	1	0	14	12	0	0	0	5
IMPACT DEFORMATION	0	0	0	0	0	0	0	0	1	1	0	2	0	0	10	0	0	0	0	0	10	0	1	0	0	0	0	0	0	0	0	0
IMPACT FRETTING	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0
IMPACT FATIGUE WEAR	0	0	1	0	0	0	0	1	0	0	1	1	1	0	7	0	0	0	0	0	1	0	10	0	0	0	0	0	0	0	0	0
INSTALLATION DAMAGE	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0
INTERGRANULAR CORROSION	1	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	1	0	1	0	0	0	0	16	0	0	11	0	0	0	2
STARVED JOINT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0
SURFACE FATIGUE WEAR	1	0	0	0	0	1	0	0	12	0	13	0	0	0	25	0	14	0	0	14	0	0	0	0	0	0	30	1	0	0	0	0
TEMPERATURE INDUCED DEFORMATION	9	1	0	0	0	21	0	17	4	0	0	2	11	0	19	0	4	3	0	12	0	1	0	0	11	0	1	159	3	0	6	23
THERMAL FATIGUE	0	0	0	0	0	0	0	3	0	0	0	0	3	0	2	0	0	0	0	0	0	0	0	0	0	0	0	3	7	0	2	1
THERMAL RELAXATION	1	3	0	0	0	0	0	0	0	0	0	2	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23	0	6
THERMAL SHOCK	0	0	0	0	0	4	0	1	0	0	0	0	3	0	3	0	0	0	0	0	0	0	0	0	0	0	0	6	2	0	11	1
YIELDING	5	10	0	0	0	5	0	23	0	0	0	8	16	5	50	1	1	0	0	5	0	0	0	0	2	0	0	23	1	6	1	136

Figure 5. Similarity Matrix.

Table 3. Cluster Grouping of Failure Modes.

CLUSTER	MEMBERS	Type
Cluster - 1	Abrasive Wear	II
	Compression Set	
	Heat Cracking	
	Installation Damage	
Cluster - 2	Adhesive Wear	II
	Deformation Wear	
Cluster - 3	Ageing	III
	Biological Corrosion	
	Blistering	
	Ductile Rupture	
	Fretting Fatigue	
	Galvanic Corrosion	
	Impact Fretting	
	Impact Fatigue Wear	
	Intergranular Corrosion	
	Starved Joint	
	Thermal Fatigue	
	Thermal Relaxation	
	Thermal Shock	
Cluster - 4	Brittle Fracture	II
	Temperature Induced Deformation	
Cluster - 5	Corrosive Wear	II
	Yielding	
Cluster - 6	Cracking	II
	Creep Stress Rupture	
	Galling and Seizure	
	High Cycle Fatigue	
	Surface Fatigue Wear	
Cluster- 7	Creep Buckling	II
	Impact Deformation	
Cluster - 8	Direct Chemical Attack	I
Cluster - 9	Force Induced Deformation	I

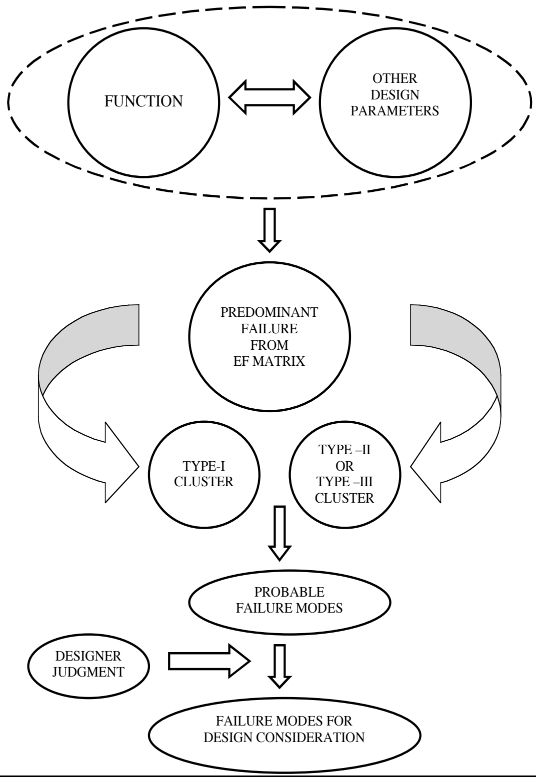

Figure 6. Schematic of the Cluster Approach.

Interpretation of the Cluster Groups

Cluster-8 and cluster-9, which have *direct chemical attack* and *force induced deformation* respectively, are single member clusters. This is because of the fact that these two failures have a very high frequency of occurrence and occur along with a variety of failure modes. Hence they are placed in an individual group so that they will be considered in all design situations. We shall call such clusters Type-I clusters.

Clusters 1, 2, 4, 5, 6, and 7 comprise failure modes that have a tendency to occur together. In cluster-1 *abrasive wear* has 74 occurrences while the other members of the cluster have a maximum of about 5 occurrences. They are still being placed in a single cluster because *abrasive wear* on most occasions occurred by itself; if it did occur with other failure modes they predominantly occurred with failure modes in cluster-1. Similarly, the failure modes in clusters 2, 4, 5, 6, and 7 have a tendency of occurring together. We will call such clusters Type-II clusters.

Cluster 3 is the group of failure modes that will be dealt with on an individual basis. These are failure modes that have a very low occurrence rate and do not show any particular characteristic of occurring along with another failure. Thus for a failure mode in cluster-3 we will consider only that particular failure mode for design. We shall call such clusters Type-III clusters. The following section explains the general steps involved in using the cluster information.

Rules for Using the Cluster Information

For identifying the failure modes to be considered during the initial conceptual design stages, a three-step approach, shown schematically in Fig. 6, is followed:

1. Clusters with single membership, that is, Type-I clusters that have only one failure mode are always considered during the initial design stage.
2. For the given function (E) under consideration, we identify the maximum occurring failure mode. This is identified from the function-failure matrix (EF). In selecting the maximum occurring failure mode from the EF matrix, the failures belonging to Type-I clusters are not considered as they are already taken into consideration in Step 1.
3. After having identified the maximum occurring failure mode, the cluster to which it belongs is identified. If the failure mode belongs to a Type-II cluster we consider the entire cluster for the

design; if the failure mode belongs to a Type-III cluster only that failure mode is considered and others are ignored.

We claim that by following Steps 1 through 3 we will identify a set of failure modes, of which the failure modes corresponding to the design in hand would be a subset. Let us denote the set of failure modes corresponding to the design under consideration by F_d and the set of failure modes obtained from Steps 1 through 3 by F_{1-3}. We claim that

$$F_d \subseteq (F_{1-3} \cup \Delta_d), \tag{3}$$

where Δ_d is the set of failures that the Steps 1 through 3 did not yield for the design under consideration. For this work, the number of failure modes that was overlooked for a given component was on average 0.295. That is $n(\Delta_d) = 0.295$. This shows that by following the failure mode clustering approach we can identify a superset of failure modes corresponding to the failure modes of the design under consideration by overlooking just about 0.295 failure mode per component. Thus Equation 3 can be closely approximated as:

$$F_d \approx F_{1-3}. \tag{4}$$

Table 4 shows the values of $n(\Delta_d)$, the number of overlooked failures. We see that on an average we overlooked about 0.295 failure mode per component. The table is interpreted as follows. First we determine the predominant failure mode for the given function. For example, take *abrasive wear*. *Abrasive wear* belongs to cluster-1. Now the component, which delivers the desired function, is designed to withstand failures belonging to cluster-1, cluster-8 and cluster-9. That is, the component is designed to counter *abrasive wear*, *compression set*, *installation damage*, *heat cracking*, *direct chemical attack* and *force-induced deformation*. (As described in the previous section, it is not necessary to consider all the failure modes provided by the clusters, and engineering judgment may be exercised in choosing the required failures from the given set of failures). Thus, when a component is designed to counter the failures in the three clusters, on average, we would have overlooked 0.55 failure per component, based on observed failure modes. For failures belonging to cluster-3, only that individual failure along with cluster-8 and cluster-9 are considered and other failures in cluster-3 are not considered (Type-III cluster), as this is a group of failures that have either occurred very infrequently or have not exhibited any particular association with another kind of failure mode. Thus the $n(\Delta_d)$ values of failure modes corresponding to cluster-3 were not calculated. So the designer may design the component for that particular failure mode, force induced deformation, direct chemical attack and any other failure thought to be pertinent to the case. As more failure mode observations are recorded in the function-failure matrices, $n(\Delta_d)$ is expected to decrease.

APPLICATION TO THE 'STOP GAS' FUNCTION

We now apply the three-step method described in the previous section to the *Stop Gas* function component.

1. We take into consideration Type-I clusters. In this case they are clusters 8 and 9 corresponding to failure modes *direct chemical attack* and *force induced deformation*.
2. For the given function we identify the maximum occurring failure mode from the function-failure matrix (EF). We find that the maximum occurring failure mode is *compression set*. Here as we had mentioned in the previous section the designer can use his/her discretion in selecting the failure mode. We select the *compression set* failure modes, as we know that it is associated with rubber failures (since we have chosen rubber seals as a solution from the morphological matrix.)
3. Next we identify the cluster to which the failure mode *compression set* belongs. It is cluster-1. As it is a Type-II cluster we consider the entire cluster for the design.

Thus our superset F_{1-3} comprises force *induced deformation*, *direct chemical attack*, *abrasive wear*, *compression set*, *heat cracking* and *installation damage*. Now the designer can use his/her judgment in analyzing the failure modes that pertain to the design from the given set.

We did a cross check with the component–failure matrix (CF) for the components identified solving the function *Stop Gas* to see what failure modes they had exhibited and if we had the value of $n(\Delta_d) <$ 0.295. Table 5 shows the failure modes in the components identified and the number of failures modes that were not identified by the cluster approach.

Table 4. n (□$_d$) Values.

FAILURE MODE	CLUSTER 1	CLUSTER 2	CLUSTER 3	CLUSTER 4	CLUSTER 5	CLUSTER 6	CLUSTER 7	CLUSTER 8	CLUSTER 9	OVERLOOKED FAILURE
ABRASIVE WEAR	x							x	x	0.550
ADHESIVE WEAR		x						x	x	0.115
AGEING			x					x	x	x
BIOLOGICAL CORROSION			x					x	x	x
BLISTERING			x					x	x	x
BRITTLE FRACTURE				x				x	x	1.147
COMPRESSION SET	x							x	x	0.000
CORROSIVE WEAR					x			x	x	0.275
CRACKING						x		x	x	0.190
CREEP BUCKLING							x	x	x	x
CREEP STRESS RUPTURE						x		x	x	0.026
DEFORMATION WEAR		x						x	x	0.156
DIRECT CHEMICAL ATTACK								x	x	x
DUCTILE RUPTURE			x					x	x	x
FORCE INDUCED DEFORMATION								x	x	x
FRETTING FATIGUE			x					x	x	x
GALLING AND SEIZURE						x		x	x	0.473
GALVANIC CORROSION			x					x	x	x
HEAT CRACKING	x							x	x	0.000
HIGH CYCLE FATIGUE						x		x	x	0.666
IMPACT DEFORMATION							x	x	x	x
IMPACT FRETTING			x					x	x	x
IMPACT FATIGUE WEAR			x					x	x	x
INSTALLATION DAMAGE	x							x	x	0.000
INTERGRANULAR CORROSION			x					x	x	x
STARVED JOINT			x					x	x	x
SURFACE FATIGUE WEAR						x		x	x	0.100
TEMPERATURE INDUCED DEFORMATION				x				x	x	0.360
THERMAL FATIGUE			x					x	x	x
THERMAL RELAXATION			x					x	x	x
THERMAL SHOCK			x					x	x	x
YIELDING					x			x	x	0.365
AVERAGE										0.295

Table 5. Verification of Failure Modes for Hypothetical Design.

COMPONENT / FAILURE MODE	ABRASIVE WEAR	COMPRESSION SET	CRACKING	FORCE INDUCED DEFORMATION	INSTALLATION DAMAGE	UNACCOUNTED FAILURE
RUBBER PISTON SEAL	0	1	0	0	1	0
O-RING	0	0	0	1	0	0
RUBBER SEAL PLUG	0	1	0	0	0	0
AIR TUBE CAP	0	0	1	1	0	1
RUBBER PRESSURE GAUGE RING	0	0	0	1	0	0
SPACER	0	0	0	1	0	0
RUBBER BARREL SEAL	1	1	0	0	0	0
AVERAGE UNACCOUNTED FAILURE/COMPONENT						0.143

As seen from Table 5, we missed just one failure mode for a single component. A careful consideration would reveal that the air tube cap was a plastic component and had we decided on a plastic component, we would have selected cracking as our major failure in Step 2 of the cluster approach and we would have still found all the failure modes for the component. This also has another advantage. We see that while all the rubber seals experienced the failure mode *compression set*, just one of them experienced *abrasive wear* and *installation damage*. Thus clustering helps in retraining collective information of failure history for given functions spanning the various components. Thus the designer would now have considered all the failure modes that such a component solving a particular function had experienced. As mentioned before if the seal is just in a home-product, then it might not be necessary to design it for *force induced deformation* or *direct chemical attack.* However, if it is in some aerospace application it would be necessary to consider these failures indicated by the Type-I clusters as seal might come in a very reactive environment with the gas possessing tremendous velocities.

CONCLUSION AND FUTURE WORK

A clustering-based method aimed at producing failure-free designs has been described to help the designer during the conceptual design stage in identifying potential failure modes and deciding which failure mode analyses are needed. The standardized vocabulary coupled with the matrix approach, introduced in Tumer and Stone [1], is used here as a basis for analyzing the statistical characteristics of failure mode data. A discussion of the advantages of using a clustering-based approach to failure mode identification and analysis planning is presented in detail including the technical approach and a hypothetical example.

The clustering method was shown to overlook less than one failure per component (0.295 failures per component on average) based on our study of 41 products. It is expected that the inclusion of additional products will reduce this value. It is important to note that our aim is a “failure-free” design methodology, though currently this approach is more accurately described as an attention directing tool. Future work will seek to eliminate the overlooked failure modes or, alternatively, quantify the risk of any overlooked failure mode.

Further research is needed to expand the failure mode classification to include more material specific failures such as the failure of composite materials and to include more failures pertaining to the variety of electrical components. The current work focused only on the occurrence data of the failure modes. The performance of the methodology with the severity and detectability data is a part of the ongoing research.

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